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Towards an automatic sunspot tracking: Swarm intelligence and snake model hybrid

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Abstract. In this paper we discuss the suitability and versatility of a computer aided approach for identification and automatic tracking of sunspots with the aim to study solar evolution of sunspots and contribute to advances in models for predicting space weather and its influence on Earth. Our work crosses the discipline boundaries of AI and Solar Physics by proposing an automatic sunspot tracking system based on a combined evolutionary Swarm Intelligence algorithm and Snake model. Some illustrative examples of tracking sunspot evolutions are presented to clarify the potential of the proposed approach.

1 Introduction

Sunspots (dark areas in the Sun's photosphere, which are cooler than their surroundings) are the easiest feature to detect from all manifestations of the solar activity. They generally appear in pairs or groups, and are associated with very strong magnetic fields. The number of sunspots varies in a cycle lasting about 11 years. The powerful magnetic fields around sunspots produce active regions on the Sun, which often lead to solar flares and Coronal Mass Ejections (CMEs). These are also called "solar storms" because they are the major drivers of space weather. Tracking of sunspots is therefore very important to follow the evolution of solar activity during a solar cycle. The evolution of sunspots was traditionally tracked by manual detections on daily drawings and/or low-resolution images taken by ground-based telescopes. However, in the last decades high-resolution data from ground-based and space-borne instruments have become available and nowadays we need more sophisticated tools to analyze huge amounts of images, hence, intelligent automatic tracking algorithms are promising tools.

This paper proposes an automatic sunspot tracking system based on an evolutionary intelligence model. The model selected is a combination of Particle Swarm Optimization [16], an emerging and promising algorithm under Swarm Intelligence, and an Active Contour Model [15], an image processing framework.

Our motivation is to discuss the suitability and versatility of using an intelligent tracking algorithm for identification and tracking of sunspots with the aim to study solar evolution of sunspots and contribute to advances in models for predicting space weather and its influence on Earth. Measuring and tracking of solar features is a key task in studies of solar activity evolution, climate change understanding and space weather prediction. For example, Koch and Wohl [17] investigated a diurnal variation of the solar rotation rate as derived from sunspot tracings. Despite the fact that sunspots move on the surface

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of the Sun in accordance to solar rotation, they also depict some proper motion in the solar photosphere [3].

This paper describes the model and the developed computer-aided software tool for tracking sunspots. The approach can be applied to image processing of large image sets such as Solar and Heliospheric Observatory (SOHO)/Michelson Doppler Imager (MDI) images and Solar Dynamics Observatory (SDO)/Helioseismic and Magnetic Imager (HMI) images - that means a direct application to space weather research. Here we demonstrated the tool with the tracking of sunspots in these two types of images to clarify the potential of this approach. Both the SOHO/MDI and the SDO/HMI instruments record full-disk photospheric activity, i.e. evolution of sunspots. The MDI and HMI images are available on a daily basis (independently from weather conditions like in case of ground-based solar instruments, therefore they are suitable for sunspot tracking problem.

The rest of the paper is organised as follows; Section 2 describes the main characteristics of space weather and explains why sunspots are key elements for studies in solar physics. In section 3 we discuss the tracking algorithm used in our work. In section 4 we present three real illustrative cases and discuss the experimental results obtained. Finally section 5 presents the conclusions of our work and points directions for future developments.

2 Space weather: Sunspots

2.1 Background

The Sun is our main source of energy but also a dangerous one: radiation, magnetic field disruption, and solar energetic particles constantly bombard the Earth's atmosphere and magnetosphere, as can be observed in Figure 1. Thus, the Sun is the main driver of the space weather [7, 12]. Moreover, the energy of the solar radiation governs a variety of processes in the interplanetary space, in the Earth's atmosphere and at its surface.

Adverse solar events can cause power grid and communication failures on Earth, wreak havoc on satellites or put astronauts at risk from radiation exposure, among other problems. For instance, when Coronal Mass Ejections (CMEs) take place, we need to worry about satellites, transformers of electricity systems, train roads, and pipelines. When we have a huge solar flare in progress, GPS signals are in danger of being obscured by solar radiation and hence operating at lower accuracy than normal. These are only a few examples of

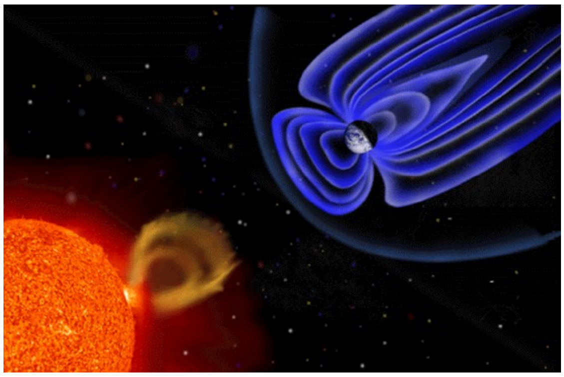

FIGURE 1. *Earth magnetosphere interacts with solar wind. (Courtesy of NASA/ESA SOHO mission)*

space weather impact on Earth's environment. To illustrate the impact in more specific terms, here are some incidents related with solar events, worthy of mentioning [10]: 1. The solar storm of 1859, also known as the Carrington Event– if such strong event occurred nowadays it would destroy most of the satellites in orbit and would cause a major technological problem in ground systems. 2. The Canada blackout in 1989 in Quebec province– severe space weather events induced ground currents that knocked out the transformers within several seconds, cutting off the power of millions of people for several hours. 3. The Japanese 640 million dollar research satellite (ADEOS-II) failed as a result of the major solar storm that pummelled Earth in the period of 22nd to 30th October 2003. ADEOS-II also had the 150 million dollar NASA SeaWinds instruments on board.

Sunspots are the easiest feature to detect from all manifestations of the solar activity. They have been observed by naked eye since ancient times. The usage of a telescope for sunspot observation by Galileo Galilei in 1610 brought a higher level scientific approach to the investigation of sunspots. Regular observations starting in the 18th century enabled us to follow the evolution of sunspots and movement due to solar rotation almost on a daily basis. One of many indices of solar activity is the so-called sunspot number [9]. Long-term statistics showed that solar activity varies in a cyclic manner. The best known and documented is the 11-year cycle that can be based on the variations of sunspots, solar flares and faculae and other features on the solar surface and in the solar atmosphere. Tracking of sunspots is therefore very important to follow the evolution of solar activity

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during its eleven-year solar cycle and also due to its correlation with other solar activity features (e.g. filaments, CMEs). Advances in understanding other solar activity processes, such as solar flares, filaments, and CMEs, will also contribute to improve knowledge about solar evolution, space weather forecasting models and ultimately designing better early warning systems.

In the last decades a huge amount of high-resolution data from ground-based and space-borne instruments (e.g. SOHO, Hinode, STEREO, SDO) have become available and nowadays we need to analyse huge amounts of images. Future space research will continue to provide huge numbers of solar images, and we need tools to manipulate them and perform data analysis; hence, intelligent automatic tracking algorithms are the natural next step in this path.

2.2 Related works

There are already some functional detection tools available e.g. in the European Grid of Solar Observation (EGSO) network, http://solar.inf.brad.ac.uk/ (as of 1 July 2011). These tools allow automated detection of sunspots, active regions and filaments on full disk solar images, however, they do not cover the tracking along time (temporal aspect), which is essential to predict solar events. Sunspots detection in white-light (WL) from the MDI instrument aboard the SOHO satellite, has been developed by Zharkova et al. [30] in the frame of the Solar Feature Catalogues (SFCs) project. Like most solar feature segmentation and tracking tools, this approach is based on classical image processing techniques such as intensity threshold, median filters and morphological operations. Moreover, the authors developed some preliminary work but only on the detection of sunspots using classic image processing techniques such as watershed algorithms [11]. In [28, 27] the authors propose an approach based on mathematical morphology to identify sunspots. This non-linear image processing technique uses shape and structure in a digital solar image, with a morphological top-hat transformation to detect sunspots.

Other proposals such as Bernasconi et al. [6] and Sobotka et al. [23], developed basic tools for automated detection, classification, and tracking of solar filaments, but these approaches are rather rudimentary. In a recent study, Barra et al. [5], proposed a method for segmentation and tracking solar features from a set of multi-spectral EIT solar corona images to analyse the spatial distribution of coronal bright points.

3 Tracking algorithm

The algorithm to be used for identification and tracking of sunspots in this study is a merger of a Snake model and Particle Swarm Optimization [22], henceforth called S-PSO. Snake model also known as Active Contour Model, is an energy minimization algorithm induced not only by low level image features such as image gradient or image intensity, but also with higher level information such as object shape, continuity of the contour and user interaction [15]. Given an approximation of the object boundary, the snake model will be able to find the precise boundary of that object. Snakes are also widely used as an interesting approach in segmentation, shape modelling, stereo matching and object tracking [14, 20, 4, 29]. The energy of snake depends on its spatial positioning on the image and on the changes in its shape. The idea is to minimize the integral measure which represents the total snake energy. Original snake model achieves this minimization by iteratively solving a pair of Euler equations on the discrete grid, resulting in a computationally expensive algorithm [14].

There are two main approaches for snake presentation; Geometric and Parametric models. Geometric models use an implicit presentation based on the curve evolution theory [8] and are usually implemented with level-set techniques. This approach is specifically more effective in handling multiple objects and topology alteration, but the computational cost is a major drawback. In this paper we use the parametric approach, which is computationally efficient and easy to interact with users [13]. In the parametric implementations, a number of discrete points called control points or snaxels characterize the snake [15]. Snake model is considered to be a controlled continuity spline under the influence of internal and external forces which induces the snake energy.

The second part of the tracking approach is the Particle Swarm Optimization (PSO) algorithm, which is an evolutionary optimization technique consisting of a number of particles, each representing a potential solution to the problem [16]. The Swarm is initialized with random solutions, i.e. random positions and velocities for the particles. In traditional PSO the number of particles remains unaltered during the evolution process. Particles fly through the hyperspace searching for the global optimum. By sharing information within the swarm, particles progressively cluster around the optima. The velocity is continuously adjusted according to the particle's experience of best position as well as its

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neighbours'. Particles remember the best position they have discovered according to a fitness evaluation function. This position and its corresponding fitness value are stored as personal best, *pbest* in short, and form the cognitive aspect of particle evolution. Second principle of particle evolution simulates social behaviour and is implemented by tracking the overall best position found within the particle neighbourhood. More details about the combined (hybrid) approach can be seen in [22].

The tracking approach used here is built on the authors' previous work (S-PSO) [21] and combines advantages of high-level object detection capacities of the snake model with the PSO algorithm to achieve a promising system for automatic sunspot tracking. The main steps of the S-PSO algorithm are as follows:

- **Step 1. Initialization.** The pre-processing of images is done if required, i.e. normalizing the size of images, correcting the orientation and contrast of images, etc.
- **Step 2. Initial Contour.** The initial contour (snake) is drawn, by an operator, around the area of interest. For most cases a rough estimation of the initial contour is enough. This step is done only once when the sunspot appears.
- **Step 3. Internal parameters set-up.** The weight parameters for the S-PSO algorithm are initialised in this step.
- **Step 4. Snake force calculation.** The external force (image force) is calculated, once for every image.
- **Step 5. Calculation of social and cognitive parts.** In this step we update the *pbest* value (the best velocity the snaxel ever experienced) and the *lbest* value as average of velocities of neighbouring particles.
- **Step 6. Moving snaxels.** For each snaxel its velocity is evaluated and then each snaxel velocity and position are updated.
- **Step 7. Snake detection.** This step checks the convergence of snake contour to the sunspot outline, i.e. choosing the snake with the lowest total energy calculated. If the results are not satisfactory, algorithm goes back to step 5. The outcome of this step is the sunspot contour for an image frame.

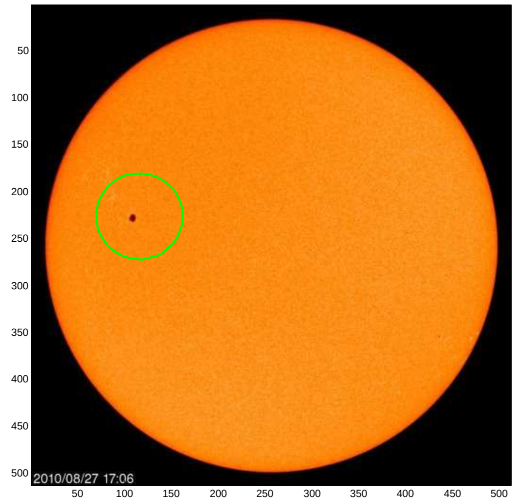

FIGURE 2. *Initial snake on first image.*

- **Step 8. Tracking sunspots.** This step tracks the same sunspot in the next image by feeding the subsequent image frame to the system as input. The algorithm loops back to step 4, and passes the specifications of the detected sunspot.
- **Step 9. Stopping tracking.** Tracking of a sunspot ends when a sunspot disappears, e.g. when it shrinks below a threshold limit, or when it reaches the solar limb.

The outcome of the detection phase (step 7) is the sunspot contour. This contour will be fed into the tracking phase (step 8) as its initial contour. In step 8 the snaxels won't be initialized since they will remember their position and properties such as speed, direction and momentum. During running time the operator can interact with the system adding or removing sunspots to be tracked.

In some recent works, evolutionary algorithms have been used with snake models to optimise snake equations [18, 19, 25]. In [22] the Snake Driven Particle Swarm Optimization model has been successfully applied for medical image processing, i.e. to detect abnormalities in brain MIR and CT images. In this paper we extended this work and proposed a tool to facilitate sunspot detection and tracking.

Other swarm based snake optimisation algorithms [19, 13, 25] determine the next position of the snaxels by searching all pixels in a predefined radius of that snaxel, while in our approach the search space

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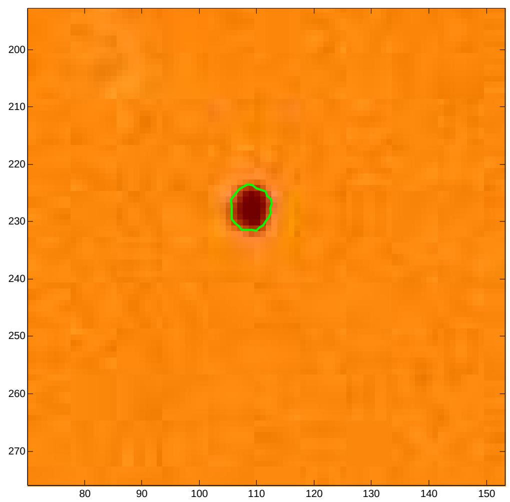

Figure 3. *Delineation of sunspot in first image.*

Figure 4. *Top– Identified sunspot at E38N12 on 2010/8/27, Middle– Tracked sunspot two days later at E12N12, Bottom– Tracked sunspot five days later at W22N12.*

is explored according to the PSO trajectory, which obviates the computationally expensive local search to be repeated in every iteration.

4 Illustrative examples

In this section the potential and performance of the proposed tracking algorithm is demonstrated with three simple illustrative examples. First example is just one sunspot for a period of 8 days. Obviously the proposed S-PSO approach is capable of tracking more than one sunspot and also tracking groups of sunspots but for clarity we only show examples with one sunspot.

The simulations were implemented in MATLAB 2009b software and tested on several MDI Continuum solar images from the Solar and Heliospheric Observatory (SOHO) archive [2]. Input images should pass through a pre-processing phase (step 1) to achieve a standard orientation and dimension [11]. However, SOHO images are already corrected and are well oriented so that the top of the solar disk is the solar north and the right side of the image is the solar west.

Hence, the input to the system is a series of consecutive solar images, taken from the SOHO archive for the period from 2010/8/27 till 2010/9/4, corresponding to 8 days [2]. The time period between two images can be from a few minutes up to a few days, in either case the internal parameters of the algorithm need to be tuned for that frame delay, because more delay corresponds to more displacement of sunspot in two successive frames.

After pre-processing the images (step 1), at the first appearance of a sunspot in an image, the user marks the whereabouts of the sunspot to be tracked (step 2). Then the S-PSO algorithm will evolve this contour to precisely delineate the sunspot (steps 3-7). The user interaction will be only in the first appearance of the sunspot (step 2). Afterwards, steps 8 and 9, the algorithm will automatically keep tracking the sunspot in the following frames to keep pace with its evolution during the period of study.

Due to the dynamic nature of S-PSO algorithm, detected contours are flexible and can conform to the changes in shape and size of the sunspots. Tracking a sunspot stops (step 9) when it reaches the solar limb and disappears into the other side of the Sun, or when the sunspot shrinks to a size smaller than a predefined threshold, according to the size and resolution of image.

Figure 2 illustrates the MDI Continuum image of Sun on August 27th 2010 at 17:06, taken from [2]. As mentioned before, the initial green circle is marked by the user (step 2). As it can be observed in Figure 2, the system is not sensitive to the user-defined initial contour and the S-PSO only needs a rough estimation of the regions of interest.

Figure 3 shows the result of the detection and the convergence of the algorithm to precisely outline the sunspot in the area defined by the operator (steps 3 to

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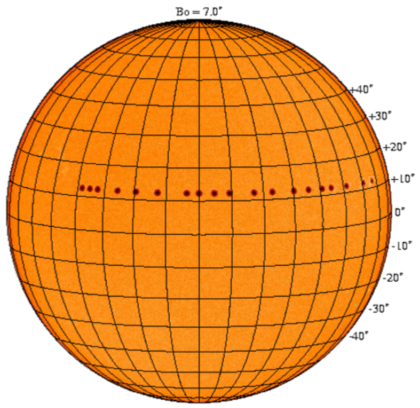

Figure 5. *Sunspot transition from 2010/8/27 till 2010/9/4 with overlaid grid.*

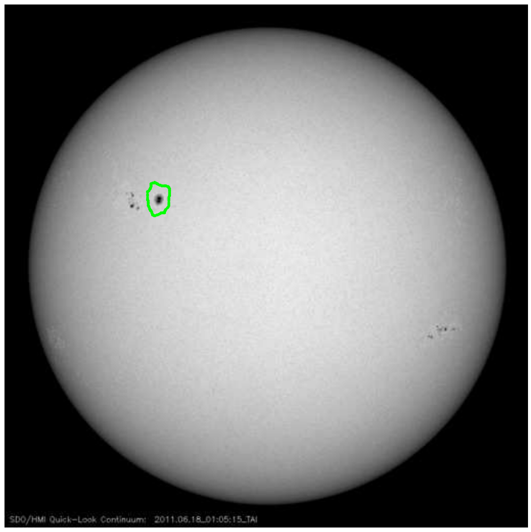

Figure 6. *Initial step in sunspot identification on HMI image from SDO.*

7). Figure 4 shows the tracking result of algorithm during 5 days, which corresponded to 22 images with an average of 6 hours interval between consecutive images (steps 8 and 9). In Figure 4, first we depict the initial detected sunspot, then we show the tracked evolution of the sunspot, and in the last image we show the result after the 5 days test period.

The whole transition of the same sunspot during 8 days is superimposed in Figure 5, under a heliographic grid with $B_0 = +7.0$ degrees. This view of the results can help space weather researchers and solar physicist to detect and track sunspots more conveniently and accurately while being able to work out new features such as analysing speed of the sunspots or studying their proper horizontal movement.

To show the usability of this system with other datasets, another experiment was carried out with SDO images, taken from [1]. Figure 6 presents an HMI Intensitygram image of the Sun on June 18th 2011, at 01:05, with initial markers drawn by operator around one sunspot of interest. Figure 7 shows the automatic identification and tracking of the same sunspot from June 18 till 24 2011.

The next example depicted in Figure 8 is a set of MDI Continuum images taken from [2] and shows the Sun on 21 till 27 of October 2003. Figure 8–Top points out a large group of sunspots in the active region AR484. It can be seen that in the following days this group shows high activity. Tracking the changing shape of this sunspot group is shown in the remaining images of Figure 8.

The algorithm results have been validated by an expert solar physicist (co-author) and the experimental results of applying the S-PSO approach to sunspot tracking shows quite promising results. Thanks to the concept of velocity of particles, the S-PSO approach is naturally well suited for the problem of tracking, and due to the freedom of particles in their movement it can handle tracking deformable shapes such as sunspots.

After, having sunspots tracked we can count them, record their coordinates on the spherical grid of the Sun, estimate their size by their contour size and also calculate their speed. These are valuable characteristics of the S-PSO tool, which can help solar physicists to obtain more knowledge about sunspots in an easier way for both new images as well as huge old archives.

5 Conclusions and future works

This paper discussed the suitability of using a computer-aided tool for tracking sunspots features, which includes a combined optimization process, based on a Snake model and the PSO evolutionary algorithm. To clarify the potential of this approach we showed three simple examples. The first one included one sunspot for a period of 8 days on SOHO MDI images. The second experiment demonstrated the performance of the algorithm on SDO HMI images, tracking a sunspot for 7

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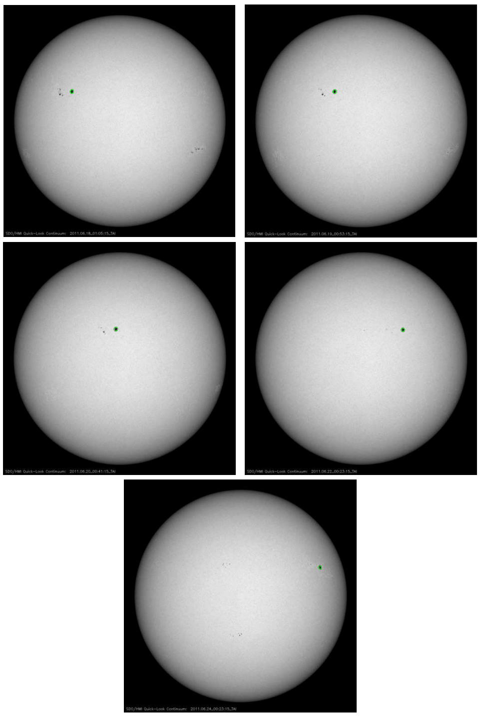

FIGURE 7. *Tracking of a sunspot in SDO HMI images from 18 to 24 of June 2011.*

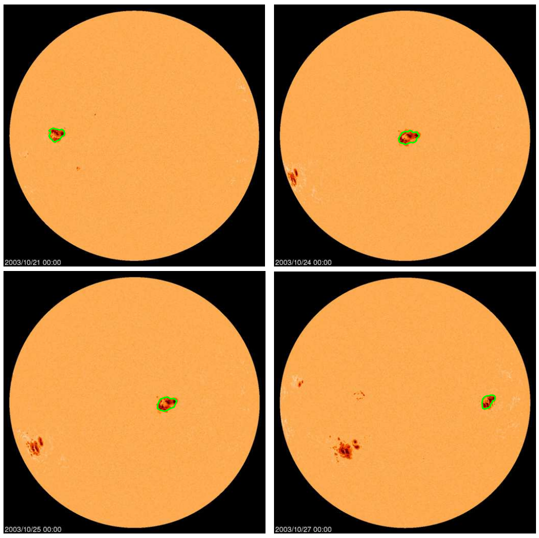

FIGURE 8. *Tracking a sunspot group in SOHO MDI images, 21 till 27 of October 2003.*

days. On the last experiment, the tracking of a group of sunspots is shown.

The obtained results confirmed that the proposed approach constitutes a promising tool for investigating the evolution of solar activity and also for processing any solar image archives. At this stage, our approach still has the limitation of the initial manual contour, where the user needs to initiate the contour around sunspots or sunspot groups. In the near future we plan to automatise this initial manual process and also to perform more tests to assess the robustness and versatility of the proposed approach. Moreover, using Stonyhurst heliographic coordinates and applying Carrington adjustments [24, 26] we can also have a more precise positioning of the sunspots.

From the space weather point of view, we plan to automatically determine the area of sunspots and/or sunspot groups, their daily displacement (angular speed of rotation), proper horizontal motion of individual sunspots, number of new and decaying sunspot groups per day, etc. All these parameters will enable space weather researchers to investigate the evolution of the solar activity over any number of solar cycles. Furthermore we also plan to apply the algorithm to the tracking of other solar features such as filaments and coronal bright points.

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